# Hand-to-Mouth Banks: Deposit Inflows and the Marginal Propensity to Lend*

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**Abstract**

In modern macroeconomics, the *marginal propensity to consume* out of transitory income shocks is a central object of interest. This paper empirically explores a parallel concept in banking: the *marginal propensity to lend* out of unsolicited deposit inflows (MPLD). Using county-level dividend payouts as an instrument for deposit inflows, I estimate the MPLD for U.S. banks and show that before QE, the average bank operated "hand-to-mouth" — it transformed approximately every dollar of deposit inflow into new loans, consistent with tight liquidity constraints. However, since then, the MPLD has dropped to 0.37. Moreover, the MPLD decreases in banks' cash-to-asset ratio and measures of deposit market power. The findings suggest that the QE-induced abundant reserves regime significantly relaxed liquidity constraints for the majority of banks, but did not eliminate them entirely.

**Keywords:** Banking, deposits, loans, money creation, reserves
**JEL Classification:** G21, E42, E51

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# 1 Introduction

The marginal propensity to consume (MPC) out of transitory income shocks is a key concept in modern macroeconomics. It measures the per-dollar consumption response to an unexpected income shock and plays a particularly important role in models with heterogeneous agents, where some agents face binding liquidity or borrowing constraints and thus cannot reach their desired consumption levels (Auclert *et al.*, 2024; Kaplan and Violante, 2014; Kaplan *et al.*, 2018). These "hand-to-mouth" agents exhibit large MPCs, as positive income shocks relax their constraints and allow them to spend more on consumption. In contrast, unconstrained "Ricardian" agents often have near-zero MPCs, as they spread any windfall income over their lifetimes. MPCs thus serve as an indicator of binding constraints and help policymakers identify the parts of the population where targeted policies (e.g., fiscal transfers) have maximum economic impact.

This paper explores a parallel concept for banks: the *marginal propensity to lend* out of unsolicited deposit inflows (MPLD). When choosing their portfolios, banks are subject to various constraints, including regulatory ones. Assuming that banks face lending opportunities with diminishing returns, an unconstrained bank should use any unexpected cash inflow to either optimize its liability structure (e.g., pay down expensive wholesale funding) or simply increase cash holdings (Stulz *et al.*, 2024). In other words, the MPLD for "Ricardian" banks should be close to zero. However, there is ample empirical evidence that unsolicited deposit inflows do affect bank outcomes, including credit supply (Cortés and Strahan, 2017; Darst *et al.*, 2025; Gilje *et al.*, 2016; Gilje, 2019; Kundu *et al.*, 2021). This suggests that some banks are, in fact, facing tight constraints. In this paper, I propose a novel instrumental variable (IV) approach based on county-level dividend payouts (Lin, 2026) to estimate the MPLD for U.S. banks and answer the question (paraphrasing Aguiar *et al.* (2025)) "Who are the hand-to-mouth *banks*?"

Understanding the distributional characteristics of the MPLD is beneficial for three key reasons: (a) policymakers can design more efficient credit easing policies that specifically target high-MPLD banks; (b) supervisors and regulators learn about which regulatory constraints are most binding; and (c) economists can target the MPLD distribution when calibrating quantitative models with heterogeneous banks.[1]

My analysis yields four key results: First, during the sample period of 1995–2021, the average MPLD is strictly positive, in line with previous local estimates. Moreover, before Quantitative Easing (QE) started in 2008, the MPLD was approximately one, i.e., the average bank

[1] See, e.g., Bellifemine *et al.* (2025); Jamilov and Monacelli (2026); Abad *et al.* (2024). I will make bank-by-bank MPLD estimates (Section 6.5) available on my website for interested researchers.

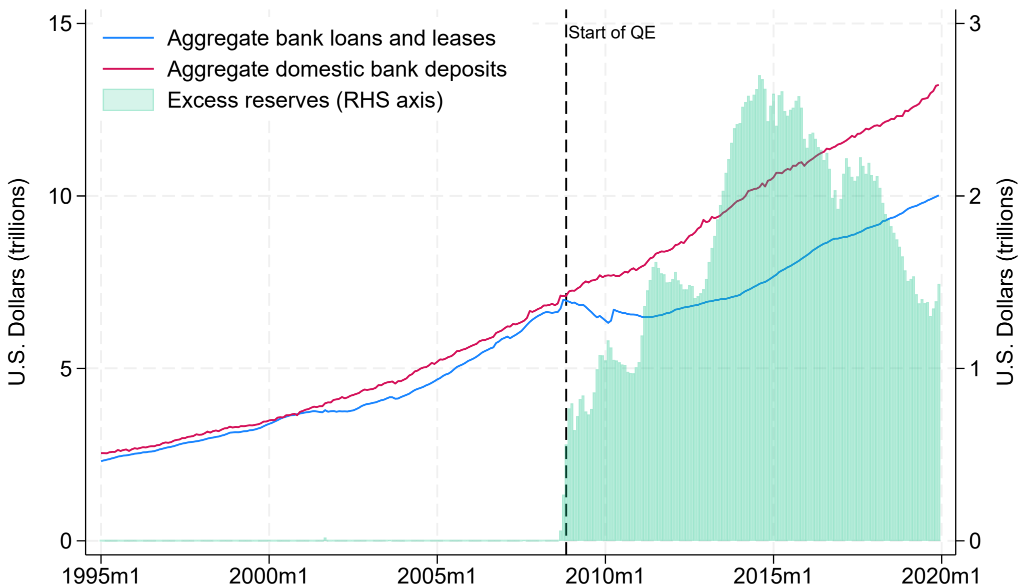


**Figure 1: Aggregate loans, deposits, and excess reserves in U.S. banks.** Monthly U.S. aggregate bank loans and leases (FRED series: LOANS), aggregate domestic bank deposits (DPSACBW027SBOG), and excess reserves of depository institutions (EXCSRESNS), January 1995 – December 2019. Loans and deposits are plotted against the left axis; excess reserves are shown as a bar chart on the right axis. All series are expressed in trillions of U.S. dollars. The vertical line marks November 2008, when the Federal Reserve launched its first round of Quantitative Easing (QE). Source: FRED (Federal Reserve Bank of St. Louis).

transformed roughly every dollar of dividend-induced deposit inflows into new credit, especially real estate loans. However, during the QE era the average MPLD dropped to 0.37 (again driven by real estate lending), which mirrors the decoupling of aggregate loans from aggregate deposits depicted in Figure 1.

Second, the MPLD is decreasing in banks' cash-to-asset ratios and deposit market power, measured by a bank's average deposit Herfindahl index (HHI) across counties. Similarly, the MPLD is increasing in banks' deposit beta (Drechsler *et al.*, 2017), i.e., banks that need to raise their deposit rates more strongly in response to Fed funds rate hikes (a measure of deposit flightiness, see Zhang *et al.* (2024)) exhibit higher MPLDs. These results jointly suggest that liquidity constraints (related to both asset liquidity and funding stability) are important determinants of "hand-to-mouth" lending behavior, and that the QE-induced abundant reserves regime relaxed these constraints for the U.S. banking sector.

Third, much of the banking literature has focused on *leverage* as the key source of constraints (e.g., in the form of regulatory minimum capital requirements). In contrast, I do not find a clear cross-sectional relationship between the MPLD and leverage (measured by the ratio of total assets to equity). This suggests that, although regulatory leverage constraints likely affect the *level* composition of banks' balance sheets, liquidity constraints are more important in explaining marginal propensities to lend.

Finally, I document that dividend-induced deposit inflows crowd out non-deposit funding and crowd in bank equity. For every $1 of deposits (and hence cash) flowing in, the average bank pays down $0.14 of non-deposit liabilities and increases equity by $0.08 (potentially in the form of higher retained earnings). The resulting $0.94 increase in total assets can be decomposed into a $0.32 increase in loans (the MPLD), $0.24 in cash, and $0.36 in securities. The fact that non-deposit funding decreases in response to dividend-induced deposit inflows lends further credibility to my identification strategy, as it suggests that banks did not actively "seek funds" to finance new lending opportunities (Plosser, 2014).

The MPLD is defined as the amount of new lending that is triggered per dollar of unexpected, unsolicited deposit inflow. The big challenge in measuring MPLDs is that bank deposits are a highly endogenous object. Banks often solicit deposits (e.g., by raising deposit rates) specifically to fund asset expansions (Ben-David *et al.*, 2017), or to support their balance sheet in times of economic slowdowns (Iyer *et al.*, 2023). Therefore, a simple regression of loan growth on deposit growth would yield biased estimates of the MPLD—not just because of reverse causality (banks create new deposits mechanically when they make loans), but also because both bank deposits and loans are driven by loan demand or common (often unobserved) macroeconomic fundamentals. If, for example, an economic boom causes both a bank's loans and deposits to grow simultaneously, a naive OLS estimate of the MPLD would be upward biased.

Therefore, based on recent research by Lin (2020, 2026), I use annual county-level *dividend income* to construct an instrument for deposit inflows. The argument is simple: When households receive dividends, they deposit at least part of this income in their bank accounts. Using FDIC data on branch-level deposits, I can allocate local dividend income to all banks within a given county in proportion to their pre-existing deposit market shares. Then, aggregating these "predicted" local flows to the bank-level yields an instrument with strong first-stage explanatory power for *actual* bank-level deposit flows, consistent with the causal county-level findings in Lin (2026).[2]

The exogeneity assumption of the dividend instrument is violated only if two conditions hold simultaneously: (a) dividend income is correlated with unobserved local credit demand

[2]Lin (2026) uses a shift-share instrument to calculate that a $1 increase in dividend income is associated with a $0.55 increase in county deposits. Moreover, he shows that "within the same bank, deposits also grow faster at branches located in areas receiving larger dividend income."

shocks at the county level; and (b) banks' lending opportunities are geographically aligned with their deposit distribution. I take several measures to alleviate each concern individually. Specifically, I use a shift-share instrument in the Bartik (1991) tradition instead of actual county-level dividend income to construct the instrument. The remaining variation in the instrument derives mostly from aggregate corporate payouts, which are orthogonal to county-level shocks. Moreover, I restrict the sample to banks that are unlikely to focus their lending business on the same counties where they raise deposits. To do so, I calculate the geographical "imbalance index" (II) from Aguirregabiria *et al.* (2025)—a measure of how strongly the geographical distribution of a bank's lending activity differs from that of its deposit-taking business—and exclude banks with an II below the median.

The findings presented in this paper have important policy implications. Obviously, knowing what effectively constrains bank lending is crucial to designing expansionary, but also contractionary policies. For example, to calibrate their quantitative tightening (QT) efforts, central banks could benefit from a better understanding of the link between the level of reserve supply and binding liquidity constraints in the banking system (Acharya *et al.*, 2023; Anbil *et al.*, 2023; Copeland *et al.*, 2025). For example, in a speech in 2023, ECB Director Isabel Schnabel emphasized that "the uneven distribution of reserves within the system, together with the large uncertainty about banks' underlying liquidity preferences, imply that central banks may have to keep a significant buffer of excess reserves in the financial system to avoid unwarranted interest rate volatility" (Schnabel, 2023). The uneven distribution of excess reserves is one way to reconcile theoretical predictions of an MPLD near zero for reserve-flush banks with a strictly positive MPLD for the average bank, even in the post-QE era (Copeland *et al.*, 2025).

Furthermore, in the current debate about central bank digital currencies (CBDC) some critics argue that retail CBDC might crowd out bank deposits and hence lead to a permanent reduction in bank lending. For instance, Greg Baer, president and CEO of the Bank Policy Institute, worries that *"given that the average loan-to-deposit ratio for banks is generally around 1:1, every dollar that migrates from commercial bank deposits to CBDC is one less dollar of lending."*[3] Recent academic work, both theoretically (e.g., by Keister and Sanches (2023)) and empirically (Whited *et al.* (2022)) confirmed that while concerns of "bank disintermediation" are warranted qualitatively, the quantitative significance might be small. My results will help understand which banks are the most deposit-sensitive, and hence most prone to potential disintermediation.

The remainder of this article proceeds as follows: The next section discusses related literature. Section 3 introduces a highly stylized model that highlights the relationship between

[3]See "Confronting the hard truths and easy fictions of a CBDC", *Business Reporter*, September 23, 2021.

liquidity constraints and the marginal propensity to lend. Section 4 then describes the dataset in detail. Section 5 explains the instrumental variable approach that produces the results presented in Section 6. Finally, Section 7 summarizes the results and briefly discusses implications.

## 2 Related Literature

This paper relates to four strands of literature. First, it speaks to a long-standing debate on bank liquidity constraints and the link between bank deposits and lending. Conceptually, this paper is closely related (and complementary) to Stulz *et al.* (2024). However, while I focus on banks' lending response, they are primarily interested in the determinants of banks' liquid asset holdings, i.e., the exact *complement* of the MPLD. Moreover, most of their analysis concerns the relationship between the *stocks* of liquid assets and illiquid loans. In contrast, this paper studies the sensitivity of lending to deposit *flows*. Stulz *et al.* (2024) show that less advantageous lending opportunities caused a steep increase in liquid asset holdings after 2008, with post-GFC regulatory changes contributing as well. These are "level effects" that are conceptually different from—and consistent with—both my model and the decrease in the MPLD after 2008 that I document in this paper.

The core theme of this paper — the excess deposit sensitivity of bank lending in times of abundant reserves — has a close counterpart in banks' intra-daily liquidity management, as documented by Afonso *et al.* (2022). They show that despite high excess reserves in the system, "the amount of payments that a bank makes in a given minute depends significantly on the amount of payments that it has received over preceding minutes." According to the authors, this behavior reveals "significant balance-sheet liquidity constraints". Although their analysis focuses on banks' incoming and outgoing payment behavior (and does not track the exact sources or targets, e.g., deposits or loans), their finding can be interpreted as a high-frequency version of the MPLD studied in this paper.

In more aggregated data, Drechsler *et al.* (2022) show that during the 1970s and 1980s, banks' average lending standards eased whenever aggregate deposit growth was high. As argued above, this is not surprising in periods of scarce reserves, i.e., when liquidity constraints are tight.

Second, this paper builds on a recent empirical literature that has developed identification strategies for exogenous shocks to banks' deposit bases. Two approaches have been particularly prominent: On the one hand, some papers (e.g., Cortés and Strahan (2017); Kundu *et al.* (2021); Thakor and Yu (2022)) exploit local natural disaster damages (in conjunction with the geographical distribution of banks' deposit activities) to construct an instrument that has predictive power for banks' deposit growth. On the other hand, Gilje *et al.* (2016), Gilje (2019), and Plosser (2014) exploit the exogenous nature of windfall incomes from oil and natural gas shale discoveries in the U.S. They demonstrate that banks with a strong presence in counties that experience shale booms enjoy deposit inflows, which increase their capacity to originate new mortgages in non-boom counties.

My approach is methodologically similar to many of these studies, but to the best of my knowledge, I am the first to explicitly estimate the per-dollar MPLD, analyze its distributional properties, and interpret it as an indicator of liquidity constraint tightness. The specific instrument I use in my analysis—local dividend income—is inspired by Lin (2026) who also used the geographical distribution of corporate equity payouts to construct bank-level deposit shocks. His results suggest that banks with a high deposit share in counties with high dividend income receive significant deposit inflows and increase lending. When comparing the three candidate local shocks, dividend income has the key advantage that it is available for every U.S. county, whereas natural disaster damage and, even more so, shale oil discoveries are much more geographically concentrated, which limits the sample of banks with usable variation and thus external validity.[4]

The first-stage logic of the dividend instrument—that dividend income partially flows into bank deposits—is consistent with a sizable household-finance literature documenting that dividend receipts are spent and saved differently from capital gains or other income. Baker *et al.* (2007) were among the first to show that consumers treat dividends as a separate mental account: the marginal propensity to consume out of ordinary dividend income is materially higher than out of comparable capital gains. Di Maggio *et al.* (2020) corroborate this using Swedish administrative data, and Bräuer *et al.* (2022) use granular German bank-account data and document that dividend payments are credited directly to depositors' accounts and trigger a sharp consumption response around the payout date, with an implied consumption rate well below one and a near-zero short-run reinvestment rate, so that a non-trivial fraction of each dividend mechanically remains in the depositor's bank account. Taken together, these papers provide direct microfoundation for the assumption underlying my instrument: county-level dividend payouts translate, at least partially, into deposit inflows at the same county's banks.

The identifying assumption of the instrumental variable approach detailed in Section 5 is further strengthened by the presence of internal capital markets by which banks allocate deposits not only locally (where depositors live), but across multiple regions. In this regard,

[4]For example, the analysis in Gilje *et al.* (2016) is limited to 7 U.S. states.

two recent articles are particularly insightful: First, Kundu *et al.* (2021) demonstrate how local natural disasters can result in large deposit outflows for multi-market banks, resulting in lending contractions that are amplified across counties through bank internal capital markets. Second, Aguirregabiria *et al.* (2025) quantify the level of geographical imbalance between banks' deposit-taking and mortgage-lending business. The "imbalance index" they propose to measure the extent of cross-county internal capital markets is a crucial input to my analysis, as it allows limiting the sample in a way that renders the IV exclusion restriction more plausible.

Third, this paper contributes to a growing body of work emphasizing the economic importance of the deposit franchise (Drechsler *et al.*, 2017, 2021; Di Tella and Kurlat, 2021; Egan *et al.*, 2022; d'Avernas *et al.*, 2023). For example, Egan *et al.* (2022) document that most of the cross-sectional variation in U.S. bank value is explained by the deposit franchise rather than by asset-side characteristics. My results speak directly to this literature: in a horse-race specification that jointly includes asset-side and liability-side MPLD covariates, the deposit-side proxies (deposit-market HHI and deposit beta) dominate the asset-side cash-to-asset ratio in explaining cross-sectional variation in the MPLD. This reinforces the view that what banks do with an unexpected dollar of funding depends more on the characteristics of that funding than on the liquidity of their existing assets.

Finally, this paper connects to a new generation of heterogeneous-banks macroeconomic models that use the term *marginal propensity to lend* in a different—but related—sense. Specifically, Bellifemine *et al.* (2025), Jamilov and Monacelli (2026), and Abad *et al.* (2024) build macroeconomic models with heterogeneous banks, analogously to seminal heterogeneous household models à la Aiyagari (1994), Bewley (1986), Huggett (1993), and Imrohoroğlu (1989). In those papers, the MPL measures the response of banks' loan supply to a change in their *net worth*, whereas in this paper the MPLD is defined in terms of shocks to the deposit base.

# 3 A Stylized Model

In this section, I introduce a highly stylized three-period bank portfolio choice problem in partial equilibrium to illustrate potential channels that can deliver a positive marginal propensity to lend.

## 3.1 Environment

At $t = 0$, a risk-neutral, profit-maximizing bank invests in illiquid loans $\ell$ and liquid cash $c$ (including central bank reserves) with returns $r_\ell(\ell)$ and $r_c$, respectively. Funding comes from an initial equity endowment $e$, deposits $d$, and wholesale debt $b$. Payoffs happen at $t = 2$, and for the sake of simplicity, I ignore default risk.

In the middle period $t = 1$, a fraction of creditors $\omega_i \in [0, 1]$ with $i \in \{d, b\}$ withdraws their funding from the bank. Assuming that liquidating loans would be prohibitively costly, these withdrawals have to be satisfied in cash. Since failure to meet the withdrawal demands would be associated with an infinite utility cost for the bank, it will always hold enough cash to pay out withdrawing creditors at $t = 1$. For simplicity, I assume that $\omega$ is known to the bank. Alternatively, $\omega$ can also be interpreted as a regulatory minimum liquidity requirement, similar to the Liquidity Coverage Ratio (LCR), a cornerstone of the Basel III regulatory framework.

On the asset side, the bank faces a downward-sloping loan demand curve with $r'_\ell(\ell) < 0$ and $r''_\ell(\ell) \leq 0$.[5] Cash yields a constant return of $r_c$, the equivalent of the Fed's interest on reserve balances (IORB).

On the liability side, the bank faces an upward-sloping deposit supply curve. Hence, to expand its deposit base, it needs to increase the deposit rate $r_d(d)$, that is $r'_d(d) > 0$. The same holds for the interest rate on wholesale funding $r_b(b)$, with the additional assumption that $r_b(0) > r_d(0) > 0$. As shown below, this assumption implies a funding pecking order, where the bank prefers deposits and only starts borrowing wholesale once the marginal cost of deposit funding reaches $r_b(0)$.[6]

The bank's profit in the final period can thus be expressed as

$$\pi = r_\ell(\ell)\ell + r_c(c - \omega_d d - \omega_b b) - r_d(d)(1 - \omega_d)d - r_b(b)(1 - \omega_b)b \tag{1}$$

In words, the bank earns the return on its loans and (remaining) cash, but has to pay interest on the remaining deposits and wholesale debt at $t = 2$. The bank chooses $(\ell, c, d, b)$ to maximize (1) given $e$ and subject to a balance sheet and a cash constraint (with associated Lagrange multipliers in parentheses), as well as respective non-negativity constraints (not shown here):

$$\ell + c \leq d + b + e \qquad (\lambda) \tag{2}$$

$$\omega_d d + \omega_b b \leq c \qquad (\theta) \tag{3}$$

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[5] This assumption can be microfounded by assuming either (a) market power over homogeneous loans, or (b) perfect screening of borrowers of heterogeneous credit quality. In the latter case, $r_\ell$ would be interpreted as the risk-adjusted return, and the bank would grant loans to borrowers in decreasing order of creditworthiness.

[6] In a model with risky loans and hence risky bank debt, the assumption could be motivated by distinguishing between insured deposits and uninsured wholesale debt.

## 3.2 Optimal portfolio allocation

The first-order conditions with respect to loans and cash imply that

$$r'_{\ell}(\ell)\ell + r(\ell) = r_c + \theta \ , \tag{4}$$

so at an interior solution the bank will choose its asset portfolio such that the marginal return on loans equals that on cash. Due to the assumptions above on $r_{\ell}(\ell)$, the left-hand side is decreasing in $\ell$.

Similarly, the first-order conditions with respect to deposits and wholesale debt imply that

$$(1-\omega_d)[r'_d(d)d + r(d)] + \omega_d(r_c+\theta) = (1-\omega_b)[r'_b(b)b + r(b)] + \omega_b(r_c+\theta) \ , \tag{5}$$

hence the marginal cost of the two funding sources will also equalize. In general, it is reasonable to assume that $\omega_d < \omega_b$, i.e., that deposits are a more "stable" source of funding than various forms of wholesale bank debt.[7] For the basic argument, however, let $\omega_d = \omega_b \equiv \omega$. Then, because of the previous assumptions on $r_d(d)$ and $r_b(b)$, the bank's funding choice will be dictated by a "pecking order": There exists a level of deposits $\tilde{d}$ such that the optimal wholesale debt $b^* = 0$ if and only if $d^* < \tilde{d}$.[8]

The first-order conditions of the problem further imply that there are two possible scenarios, depending on whether the cash constraint in (3) is binding at the optimum or not. If it is slack, i.e., if $c^* > \omega(d^* + b^*)$ (and hence $\theta = 0$), we have

$$r'_{\ell}(\ell)\ell + r(\ell) = r_c = r'_d(d)d + r(d) \ , \tag{6}$$

so the marginal returns on both assets equal the marginal funding cost. In this case, I call the bank lending decision *unconstrained*. The exogenous interest on reserves, $r_c$, pins down the optimal loan level $\ell^*$ and the optimal deposit (and potentially wholesale debt) levels $d^*$ and $b^*$ via the previous equations. The balance sheet constraint (2) then determines the optimal level of reserves $c^*$ as a residual.[9]

[7] For instance, Egan *et al.* (2025) empirically document "sleepy depositor" behavior in the U.S., and show how the resulting stickiness of deposits is the main driver of value creation in U.S. banks (Egan *et al.*, 2022).

[8] $\omega_d < \omega_b$ would make deposits even more preferable to wholesale debt, thus strengthening the pecking order.

[9] Through the lens of this model, the finding by Stulz *et al.* (2024) that "bank liquid asset holdings grew since the GFC because of weak lending opportunities" can be interpreted as a downward shift in the marginal revenue curve in Figure 2.

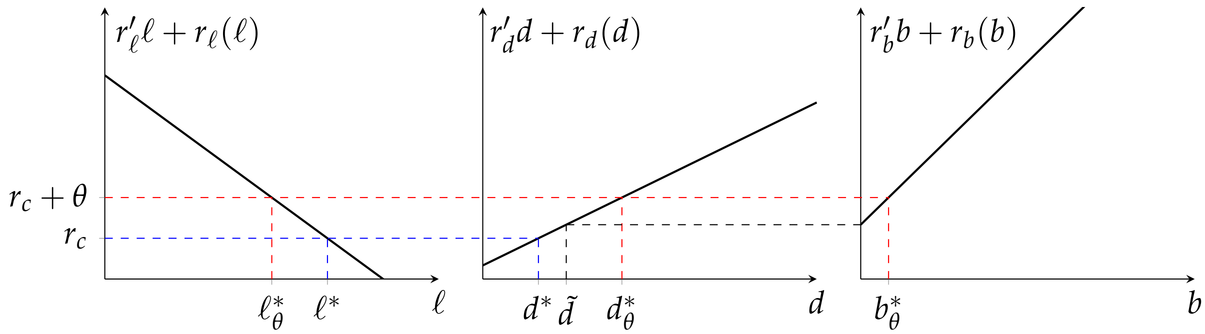



**Figure 2: Graphical illustration of optimal portfolio choice.** Each panel shows a first-order condition from the bank's static portfolio problem. *Left:* marginal revenue of loans $r'_\ell \ell + r_\ell(\ell)$ (downward-sloping) against loan quantity $\ell$. Blue dashed lines mark the unconstrained optimum $\ell^*$, where marginal loan revenue equals $r_c$; red dashed lines mark the constrained optimum $\ell^*_\theta < \ell^*$, where the shadow cost $\theta > 0$ drives a wedge between the two. *Center:* marginal cost of deposits $r'_d d + r_d(d)$ (upward-sloping) against deposit quantity $d$, with $d^*$ (unconstrained), $\tilde{d}$ (pecking-order threshold beyond which wholesale funding is cheaper), and $d^*_\theta$ (constrained). *Right:* marginal cost of wholesale debt $r'_b b + r_b(b)$ (upward-sloping) against $b$, with the constrained optimum $b^*_\theta$.

If, however, the cash constraint is binding at the optimum, (4) implies that there will be a wedge $\theta > 0$ between the marginal return on loans and that on cash, $r_c$. Compared to the unconstrained scenario, a *constrained* bank will choose a lower level of loans $\ell^*_\theta$, and a higher level of deposits $d^*_\theta$ (and potentially wholesale debt $b^*_\theta$), even though this increases its marginal cost of funding.[10] In other words, absent the constraint, the bank would prefer to invest more in loans and less in cash (see Figure 2).

### 3.3 Deposit shocks

To illustrate the effects of a positive deposit shock, suppose now that between $t = 0$ and $t = 1$, the bank receives an unexpected inflow of $\Delta d$ deposits (and a corresponding increase in reserves $\Delta c$ of the same amount), to be remunerated at the same deposit rate $r_d$. In response, it can re-optimize the remaining balance sheet. Importantly, $\Delta d$ is to be interpreted as an *inframarginal* funding shock, i.e., it does not change the bank's marginal funding cost.

Starting from the optimal balance sheet at $t = 0$, the increase in deposits $\Delta d = \Delta c$ relaxes the liquidity constraint in (3). If the bank was initially unconstrained ($\theta = 0$), the bank will keep the entire inflow $\Delta c$ as reserves (as the marginal returns on reserves and loans were already equalized). Only if the bank was initially constrained ($\theta > 0$), it would now increase its loan supply towards $\ell^*$, implying a positive MPLD. If the difference between the constrained and

[10] This is in line with the empirical result in Bechtel *et al.* (2023) that borrowers that are more exposed to urgent liquidity needs are willing to pay a markup for immediate funding.

unconstrained optimal loan supply is larger than the deposit inflow $\Delta d$, the model-implied MPLD would be exactly1.

Either way, the bank can now repay expensive wholesale funding and thus reduce interest expenses while maintaining a weakly higher revenue level than before the shock. This re-optimization echoes the observation in Plosser (2014) that a "positive lending sensitivity [to unsolicited deposit inflows] is considered a rejection of the Modigliani-Miller proposition, as unconstrained firms should invest inframarginal funding in lowering their marginal cost of capital."

Note that the model above does not include a capital constraint, which is arguably the most important regulatory constraint for banks. However, since cash holdings carry a risk-weight of zero in Basel III, a deposit (and equivalent cash) inflow would not change the bank's risk-weighted assets and thus have no effect on a potential capital constraint.[11] Therefore, although a binding capital constraint would certainly affect the bank's optimal portfolio choice, it would not change the main mechanism through which a deposit shock can increase lending in the model above.

Summing up, this simple model generates two testable implications: (a) the MPLD is positive only for banks that are initially liquidity-constrained,[12] i.e., those with $\theta > 0$; and (b) *ceteris paribus*, the tightness of the liquidity constraint (and thus the MPLD) is higher for banks with lower cash holdings $c$ and higher expected liquidity outflows $\omega$. In the next section, I attempt to identify these parameters' counterparts in bank-level data and estimate whether they are associated with a higher MPLD.

# 4 Data

The main datasets used in this paper are publicly available and sourced from three U.S. institutions: the *Federal Deposit Insurance Corporation* (FDIC), the *Internal Revenue Service* (IRS), and the *Consumer Financial Protection Bureau* (CFPB).

[11] Even the non-risk weighted so-called Basel III "leverage ratio" requirement has in the past often treated cash and cash equivalents as exempt.

[12] Methodologically, this prediction — that truly constrained banks should respond more strongly to a constraint-relaxing shock — is similar in spirit to Farre-Mensa and Ljungqvist (2016), who test whether firms classified as "financially constrained" by popular indices (e.g., the Kaplan-Zingales index) actually behave as such after tax reforms that incentivize higher debt. The key difference is that in their setting the shock is expected to elicit a *muted* response from truly constrained firms, whereas in my setting the deposit inflow relaxes the constraint, so truly constrained banks should respond *more* strongly (i.e., exhibit a higher MPLD).

## Bank balance sheet data

First, I retrieve quarterly balance sheet data for the universe of FDIC-insured institutions from the FDIC BankFind Suite, which provides standardized access to *Federal Financial Institutions Examination Council* (FFIEC) Call Report data for all FDIC-insured institutions. This includes data on each bank's total assets, loans (incl. a breakdown into real estate, commercial & industrial, consumer, and other loans), deposits, securities, cash holdings (incl. central bank reserves), and leverage (defined as total assets divided by total equity). Throughout the analysis, banks are identified by their unique FDIC Certification ID.

## County-level bank deposit data

Second, I keep only end-of-year observations for the period 1994–2021 and merge them with annual information (always as of June 30) about each bank's distribution of deposits across branches, provided by the FDIC's *Summary of Deposits* (SOD).[13] This allows me to compute (a) deposit market shares for each bank in each county, and (b) Herfindahl indices (HHI) as the sum of squared market shares within each county. Moreover, bank-level HHIs—a measure of deposit market power—are computed as within-bank averages across county HHIs, weighted by banks' deposit share in each county (Drechsler *et al.*, 2017). For more details on the geographical distribution of bank deposits, see Appendix A.

I also use the SOD data to identify complete bank mergers and acquisitions. Specifically, I flag the acquiring bank's observation in any year in which it gains branches from a bank that subsequently disappears from the data, and drop these bank-year observations because the resulting discontinuous jump in the acquirer's total loans and deposits is not organic growth and would introduce noise into the MPLD estimation.

## Dividend income data

Third, I add annual IRS data on county-level gross dividend income reported by residents in their tax returns, i.e., dividend income before subtracting any exclusions. In principle, this variable includes not just dividends distributed by publicly traded companies, but also by privately owned C-corporations. However, according to Chodorow-Reich *et al.* (2021), equity in privately

[13]Deposits are usually assigned to branches based on the account holder's address, branch activity, or where the account was opened.

owned C-corporations accounts for less than 7% of total C-corp equity. Therefore, the fraction of dividends from privately owned C-corporations in the IRS data is likely small.[14]

Figure 3 shows that (a) there is substantial heterogeneity in dividend income across counties, and (b) total dividend income in the U.S. has grown substantially since the mid-1990s, which motivated the research by Lin (2020, 2026). County-level dividend income will serve to construct a bank-level instrument for deposit inflows, as detailed in Section 5 below.

## Deposit beta data

Fourth, I also add (time-invariant) bank-level estimates of deposit betas from Philipp Schnabl's website (Drechsler *et al.*, 2017, 2021). A bank's deposit beta measures the sensitivity of its deposit rates to changes in the Fed funds rate and is a common proxy for the "flightiness" of deposits, as low-beta banks tend to have "stickier" depositors by revealed preference (Zhang *et al.*, 2024).[15] The sample covers all commercial banks with at least 40 quarterly observations in the years 1984–2022, which explains why not all banks in my sample are matched to a deposit beta.

## Mortgage origination data

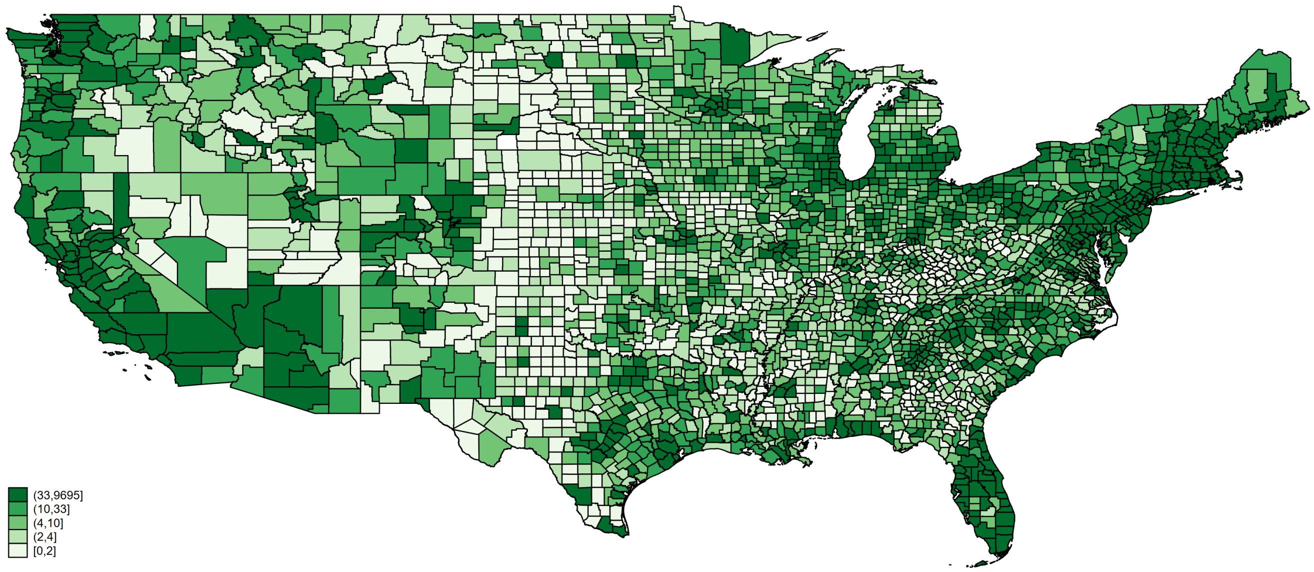
Fifth, I obtain loan-level mortgage origination records from the Home Mortgage Disclosure Act (HMDA), which requires most U.S. depository institutions to report every mortgage application and its outcome. I retain only loans classified as originated by FDIC-insured institutions and aggregate them to the bank-county-year level. This county-level mortgage panel serves as the lending-activity input to the imbalance index described below.

## Imbalance index

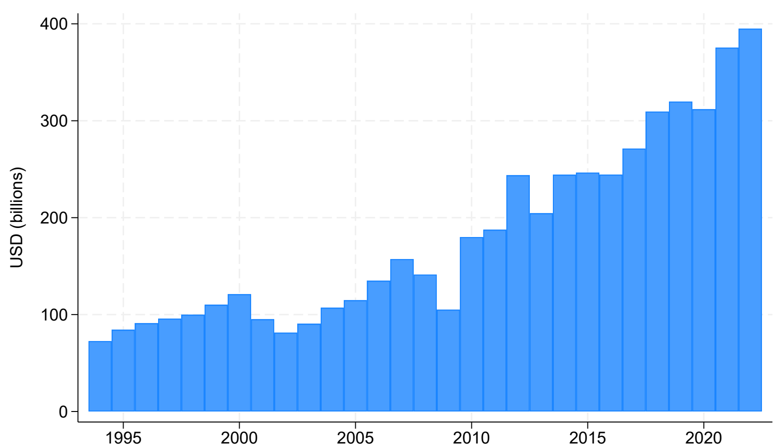
Finally, following Aguirregabiria *et al.* (2025), I construct an "imbalance index" (II) for each bank-year in my sample using the HMDA mortgage origination data and the FDIC SOD deposit data described above. The II measures the extent to which a bank's geographic distribution of mortgage lending differs from its geographic distribution of deposit-taking, and ranges from 0 (perfect geographic overlap) to 1 (complete geographic segregation between lending

[14]This detail is important for my identification strategy, as private corporations are often headquartered in the same county as their owners. Hence, they may introduce a positive correlation between dividends and business loan demand within the same county.

[15]For a thorough discussion of the relationship between deposit flightiness and betas, see also Blickle *et al.* (2024).




**(a)** Annual dividend income (mln USD) across U.S. counties (2013)




**(b)** Total U.S. dividend income over time

**Figure 3: U.S. gross dividend income.** Panel (a) is a map of annual gross dividend income (millions of USD) across U.S. counties in 2013, shaded in five quantile categories. Panel (b) is a bar chart of total U.S. gross dividend income (billions of USD) aggregated across all counties for each year in the sample period 1994–2022. Dividend income is the sum of gross dividends reported by individual tax filers in a given county and year, before any exclusions, sourced from the IRS Statistics of Income (SOI) county-level dataset.

and deposit activities). My estimates replicate Aguirregabiria *et al.*'s published values with a correlation above 0.99 for the overlapping sample period, confirming the accuracy of the construction. See Appendix B for a formal definition and further construction details.

The II allows me to restrict the sample to only banks with sufficiently strong internal capital markets that transfer deposits across county borders, which strengthens the exclusion restriction of my IV approach.

### Final dataset and summary statistics

The final dataset is an annual unbalanced panel that covers 13,977 U.S. banks over the period 1994–2021. I trimmed the dataset at the 1$^{st}$ and 99$^{th}$ percentile in terms of asset, loan, and deposit growth rates within each year to remove outliers. Additionally, key control variables (leverage, cash-to-asset ratio, HHI) are winsorized at the unconditional 1$^{st}$ and 99$^{th}$ percentile. Table 1 contains summary statistics on all variables used in the analysis.

Panel A of the table reveals, among other things, that the size distribution of U.S. banks (in terms of total assets) is heavily skewed; there are many relatively small banks (the median bank's balance sheet size is only $124 million), but also a few very big players with total assets of more than $2 trillion. Since these very large banks also have larger absolute loan and deposit growth (and larger variance thereof), observations will be weighted by inverse lagged total assets in all regression specifications, as detailed further below.

Furthermore, the table shows that for the median bank, domestic bank deposits constitute more than 80% of total balance sheet size, and thus an even larger share of total liabilities. This shows that despite a variety of other liabilities (e.g., repo borrowing), deposits are the single most important source of funding for U.S. banks.

Moreover, the table and Figure 4 illustrate that banks are, on average, geographically not very diversified in terms of their deposit-taking business. The majority of banks operates very locally, with more than half of all banks raising deposits in just one single county.[16] However, similar to bank size, this distribution has a very long right tail, with some banks operating in hundreds of counties across the U.S. In much of the following analysis, the focus will be on those geographically diversified banks.

Although this paper uses data on the geographical distribution of banks' *lending* activities only as a sample-restriction input (via the imbalance index described above) rather than as an outcome or regressor, recent work by Aguirregabiria *et al.* (2025) shows that it is considerably

[16]This development is partly driven by the secular trend in bank branch closures documented by Keil and Ongena (2024) and Narayanan *et al.* (2025).

**Table 1: Summary Statistics**

This table reports summary statistics for the main variables used in the analysis. Panel A covers the bank-year panel; Panel B covers the county-year panel. Bank-level variables include total assets, net loans, real estate loans, commercial & industrial (C&I) loans, consumer loans, cash holdings, total deposits (all in millions of USD), leverage (total assets divided by total equity), cash-to-asset ratio, number of counties in which the bank raises deposits, number of branches, bank-level Herfindahl index (HHI, computed as the deposit-share-weighted average of county HHIs), deposit beta (Drechsler *et al.*, 2017), mortgage origination, and imbalance index (Aguirregabiria *et al.*, 2025). County-level variables include dividend income (millions of USD), number of branches, number of banks, and HHI. The sample is an unbalanced annual panel of 13,977 FDIC-insured banks over 1994–2021, trimmed at the 1st and 99th percentile of asset, loan, and deposit growth rates within each year.

| Panel A: Bank level | | | | | | |
|---|---|---|---|---|---|---|
| | N | Mean | SD | p5 | p50 | p95 |
| Total assets (USD mln) | 205,507 | 1434.96 | 31786.32 | 21.19 | 123.69 | 1465.41 |
| Total loans (USD mln) | 205,507 | 777.94 | 14186.81 | 10.25 | 76.28 | 979.00 |
| Real estate loans (USD mln) | 205,507 | 413.23 | 6395.32 | 4.06 | 53.10 | 708.18 |
| Commercial & industrial loans (USD mln) | 205,507 | 156.12 | 3350.78 | 0.06 | 7.96 | 133.13 |
| Consumer loans (USD mln) | 205,299 | 128.82 | 2968.55 | 0.27 | 3.79 | 51.48 |
| Mortgage origination (USD mln) | 85,006 | 195.53 | 2613.51 | 1.13 | 16.16 | 323.66 |
| Total cash and interbank balances (USD mln) | 205,507 | 140.23 | 4578.37 | 0.90 | 6.26 | 85.45 |
| Total domestic deposits (USD mln) | 205,507 | 947.71 | 19984.62 | 17.84 | 103.54 | 1144.98 |
| Dividend exposure (USD mln) | 205,507 | 20.13 | 444.32 | 0.21 | 1.88 | 30.84 |
| Total assets / Total equity | 205,299 | 10.16 | 2.78 | 5.74 | 10.09 | 14.77 |
| Cash / Total assets | 205,507 | 0.07 | 0.06 | 0.02 | 0.05 | 0.21 |
| Number of counties with deposits | 205,507 | 2.89 | 14.19 | 1.00 | 1.00 | 7.00 |
| Number of branches | 205,507 | 9.33 | 94.78 | 1.00 | 3.00 | 19.00 |
| Bank HHI | 205,507 | 0.21 | 0.12 | 0.08 | 0.18 | 0.46 |
| Deposit $\beta$ | 168,272 | 0.37 | 0.09 | 0.23 | 0.36 | 0.52 |
| Average Imbalance Index (II) | 135,355 | 0.38 | 0.20 | 0.10 | 0.35 | 0.78 |
| **Panel B: County level** | | | | | | |
| | N | Mean | SD | p5 | p50 | p95 |
| Number of branches (per county) | 90,196 | 27.41 | 68.34 | 2.00 | 10.00 | 110.00 |
| Number of banks (per county) | 90,196 | 8.37 | 9.20 | 2.00 | 6.00 | 23.00 |
| HHI | 90,196 | 0.32 | 0.21 | 0.11 | 0.26 | 0.87 |
| Dividend income (USD mln) | 90,196 | 57.84 | 314.15 | 0.51 | 5.71 | 213.99 |

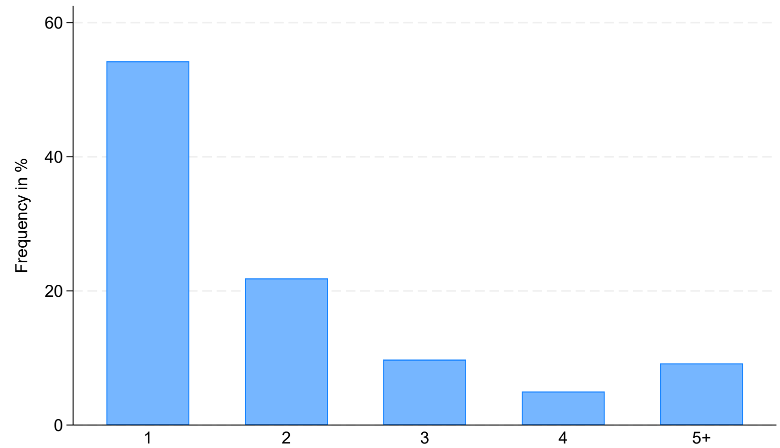



**Figure 4: Number of counties in which banks raise deposits.** Bar chart showing the distribution of bank-year observations by the number of U.S. counties in which a bank has at least one branch with deposits. Categories are 1, 2, 3, 4, and 5 or more counties. The $y$-axis reports the share of observations (in percent). Source: FDIC Summary of Deposits (SOD), 1994–2021.

more diversified than the deposit business. In their sample, the average and median number of counties per bank with mortgage lending activity are 30 and 8, respectively. Therefore, even the median bank that sources deposits from just one county faces potential loan demand from at least 8 counties. This observation mitigates the concern that the estimated MPLD might be driven by local loan demand instead of deposit inflows.

At the county level, there is also significant heterogeneity in terms of bank activity. As shown in panel B, the average county hosts 27 branches from 8 different banks, but the median is only 10 branches. This heterogeneity translates into vastly different levels of deposit concentration between counties, as measured by the Herfindahl index (HHI). A county's HHI is computed as the sum of squared bank market shares in terms of deposits, and it theoretically ranges from $1/N_c$ (where $N_c$ is the number of banks active in a county) to 1 (a local monopoly).

# 5 Empirical Strategy

A first naive approach to estimating the marginal propensity to lend out of deposit inflows (MPLD) would be to run the regression

$$\Delta Loans_{bt} = \alpha_b + \gamma_t + \beta\, \Delta Deposits_{bt} + \varepsilon_{bt}, \tag{7}$$

where $\Delta Loans_{bt}$ and $\Delta Deposits_{bt}$ are changes in total loans and total deposits of bank $b$ in year $t$, $\alpha_b$ and $\gamma_t$ are bank and time fixed effects, and $\beta$ measures the MPLD.

Bank fixed effects help to account for time-invariant differences between banks, e.g., related to size. However, in the face of the above-described skewed bank size distribution, the very largest banks also have a higher absolute variance of loan and deposit growth. Therefore, deviations from their within-bank means remain much larger than for small and medium-sized banks, and noise among these banks might significantly affect the estimation.

A standard choice in many empirical banking papers to account for this scale dependence would be to normalize both loan and deposit growth by, e.g., lagged total assets or deposits. In my case, however, this normalization would change the interpretation of the $\beta$ coefficient to something that no longer corresponds to the definition of the MPLD as the *per-dollar* lending response to a deposit inflow. Therefore, I instead weight all observations by lagged inverse total assets in all subsequent regressions. This choice allows me to correct for the inherent heteroskedasticity without dropping the largest banks from the estimation entirely.[17]

Obviously, the regression in (7) would lead to a biased estimate for the MPLD, for at least two reasons: First, there is built-in reverse causality running from loan growth to deposit growth because every dollar of new loans instantly creates a dollar of new deposits in the borrower's bank account (Faure and Gersbach, 2021; Jakab and Kumhof, 2015). Usually, these newly created deposits are quickly deployed to pay for goods or services, and hence transferred to the balance sheets of the recipient's bank. However, in areas with high deposit concentration, the likelihood that the recipient has his account at the same bank is non-negligible, which strengthens the reverse causality concern.[18]

Second, both loan and deposit growth are driven by macroeconomic fundamentals. In a boom, both the supply of deposits to banks and the demand for bank loans tend to increase, and vice versa in a recession. Similarly, when banks face increased loan demand, they may also try to actively attract deposits, e.g., by offering higher rates (Ben-David *et al.*, 2017; Iyer *et al.*, 2023). Therefore, observed increases in bank lending cannot be causally attributed to deposit growth.

Fortunately, it is well-established that banks cannot perfectly control the size of their deposit stock, since deposits are constantly used for payment purposes and circulate within the banking system (Bianchi and Bigio, 2022; Bolton *et al.*, 2025; Li *et al.*, 2024; Parlour *et al.*, 2022).

[17] Results from an *unweighted* estimation are qualitatively similar, but deliver smaller (and more noisy) MPLD estimates, since large banks generally exhibit smaller MPLDs, as shown below.

[18] The same argument explains (as pointed out by Cooperman *et al.* (2023)) a major advantage of large banks: For every loan they create (incl. credit lines), a much smaller fraction must be funded, compared to smaller banks.

Of course, banks account for some of this churn in their daily liquidity management. However, certain unexpected events, such as natural disasters (Cortés and Strahan, 2017; Kundu *et al.*, 2021; Thakor and Yu, 2022) or the discovery of shale oil (Gilje *et al.*, 2016; Gilje, 2019), have been shown to significantly affect bank deposits. Although the random nature of these shocks allows clean identification of causal effects, they are also period-specific and limited in terms of geographic scope. Therefore, based on recent research by Lin (2020, 2026), I use annual county-level *dividend income* to construct an instrument for deposit inflows.

The key advantage of dividend income—besides broad availability—is that, unlike other local statistics that affect deposit flows (e.g., unemployment), it is not primarily determined at the county level, but in corporate headquarters across the country.

Specifically, I define the instrument as

$$Dividends_{bt} = \sum_i Dividends_{it} \times \frac{Deposits_{bi,t-1}}{Deposits_{i,t-1}}, \tag{8}$$

where $Dividends_{it}$ represents dividend income in county $i$ in year $t$, and $Deposits_{bi,t-1}$ is the amount of deposits of bank $b$ held in branches in county $i$ in the previous period. The denominator in the last term measures total bank deposits in a given county, so the fractions can be interpreted as (lagged) local deposit market shares. The instrument thus constructed has an intuitive economic interpretation: It is the amount of new deposits that the bank would receive if (a) all dividend income were to flow into deposit accounts, and (b) the dividend income was allocated to banks according to pre-existing market shares.

Of course, local market shares are not exogenous to banks. On the contrary, banks might specifically penetrate markets where they expect high deposit growth to fund asset expansions. To address this concern (and thus strengthen the exogeneity of the dividend instrument), I use time-averaged market shares, $\frac{1}{T}\sum_{t=0}^{T}\frac{Deposits_{bi,t}}{Deposits_{i,t}}$, for each bank-county pair. However, results remain qualitatively unchanged if I use (time-varying) lagged market shares as in (8).

The first stage of the 2SLS approach can be represented as follows, where I regress bank-level deposit growth on the bank-specific instrument defined in the previous equation:

$$\Delta Deposits_{bt} = \alpha_b + \gamma_t + \theta\ Dividends_{bt} + \epsilon_{bt} \tag{9}$$

Of course, some counties systematically receive higher dividend income than others, e.g., because of larger populations or higher stock market participation. Consequently, banks with a strong presence in these counties will have systematically higher predicted deposit inflows than others. Bank fixed effects absorb these time-invariant differences between banks, so that most of the variation in the instrument comes from within-county fluctuations in dividend income over time. Similarly, year fixed effects account for the fact that corporate payout is cyclical and often coincides with strong deposit and loan growth across the U.S. economy.

The second stage, in turn, regresses $\Delta Loans_{bt}$ on the predicted values $\Delta\widehat{Deposits}_{bt}$ from the first-stage regression, so it exploits only the variation in deposit growth that is due to the instrument and thus arguably exogenous to loan growth. The exclusion restriction requires that the instrument is correlated with banks' loan growth *only* via deposit flows. In this specific case, threats to identification have two components:

First, it is possible that county-level dividend income is correlated with local loan demand. For example, one might worry about an increased demand for higher mortgages (or home equity loans) in counties that experience a particularly "good" year in terms of dividend income. Similarly, high dividend payouts might coincide with high local business loan demand, especially in counties where dividends originate from a large local firm.

Second, banks' lending business might be geographically very correlated with their deposit-taking activity. Only if both conditions are met—correlation between unobserved local credit demand shocks and dividend income, and lack of cross-county internal capital markets—will my bank-level instrument be contaminated by unwanted loan demand effects, and the resulting IV estimate will still be upward biased.

I address this two-stage threat to instrument exogeneity in two ways. First, I perform a shift-share projection in the spirit of Bartik (1991): Instead of actual dividend income, the annual dividend income per county that is allocated to local banks (the term $Dividends_{it}$ in equation (8)) is calculated as total U.S. dividend income multiplied by each county's lagged share in total dividend income. As a result, the intertemporal variation in projected county-level dividend income is largely driven by aggregate corporate equity payouts, which should be exogenous to a given county (Lin, 2026).

Second, and more importantly, I restrict the sample to only banks that do not concentrate their credit and deposit business in the same counties. Of course, this restriction comes at the cost of sample size and external validity, since it removes the vast majority of small, local U.S. banks. To navigate this tradeoff, I use the "imbalance index" by Aguirregabiria *et al.* (2025) and limit the sample to banks with an average imbalance index above the median (which corresponds to a value of approx. 0.35). However,I also document (in Table A1) how the OLS and IV estimates change and how potential bias is reduced when increasing the cutoff gradually from the $25^{\text{th}}$ to the $75^{\text{th}}$ percentile.

**Table 2: Estimating the Marginal Propensity to Lend (MPLD)**

This table contains the results of panel IV regressions at the bank-year level of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks that have a geographical imbalance index (Aguirregabiria *et al.*, 2025) above the median. *PostQE* is a binary indicator equal to 1 for all years from 2008 onward, and 0 otherwise. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD).

| | OLS | First-stage | IV | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $\Delta Loans$ | $\Delta Deposits$ | $\Delta Loans$ | $\Delta Loans$ |
| $\Delta Deposits$ | 0.408*** | | 0.322*** | 1.015*** |
| | (0.0504) | | (0.0581) | (0.116) |
| Dividend exposure | | 3.224*** | | |
| | | (0.288) | | |
| PostQE=1 $\times$ $\Delta Deposits$ | | | | -0.641*** |
| | | | | (0.0720) |
| Time FE | ✓ | | ✓ | ✓ |
| Bank FE | ✓ | | ✓ | ✓ |
| F | 66 | 125 | 31 | 41 |
| N(Banks) | 3,807 | 3,807 | 3,807 | 3,807 |
| N | 66,190 | 66,190 | 66,190 | 66,190 |

Standard errors (clustered at the bank-level) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# 6 Results

## 6.1 Estimating the average MPLD

Table 2 displays the results of the weighted OLS regression from Equation (7), along with the first and second stages of the 2SLS procedure. The sample is restricted to banks with an above-median geographical imbalance index. Column (1) confirms the positive association between deposit and loan growth documented in the aggregate, suggesting a bank-level MPLD of around 0.41. However, the estimate is likely biased, as discussed above. Column (2) demonstrates that the dividend instrument has high predictive power for the endogenous regressor—banks exposed to higher dividend income counties enjoy larger deposit inflows. Finally, column (3) contains the IV estimate of the average MPLD. Of every $1 a bank receives in deposits, it lends out $0.32. This number is smaller than the OLS estimate (consistent with the expected upward bias of the latter), but still strictly positive.[19] Through the lens of the stylized model in Section 3, this suggests that the average U.S. bank faces binding liquidity constraints which are relaxed by unsolicited deposit inflows. The following tests serve to confirm this interpretation.

Of course, the average MPLD is not necessarily constant over time. In contrast, it should adjust in response to regulatory changes or monetary policy regimes. In this context, it is natural to hypothesize that the regime of abundant reserves that followed QE (see Figure 1) *relaxed* liquidity constraints in the banking system, leading to lower average MPLDs. On the other hand, the post-QE era also coincided with reforms that imposed *tighter* regulatory liquidity constraints, such as the Liquidity Coverage Ratio (LCR) in the context of Basel III that was adopted in 2014 and became binding in 2017. Moreover, as Blickle *et al.* (2024) point out, QE's reserve expansion coincided with the entry of more rate-sensitive depositors, which made the average depositor more flighty. As a consequence, liquidity constraints might effectively still be tight despite high aggregate excess liquidity. Whether the net effect is a relaxation or tightening of liquidity constraints is an open empirical question that this paper addresses.

It is therefore instructive to estimate the MPLD separately for the periods before and after the start of QE in 2008. The IV estimates in column (4) of Table 2 suggest that (a) the MPLD in the pre-QE period was approximately one, and (b) the MPLD has dropped considerably since the start of QE, consistent with the interpretation of relaxed liquidity constraints.

## 6.2 Bank heterogeneity in MPLDs

To further investigate whether liquidity constraints are a determinant of the MPLD, in this section I explore cross-sectional heterogeneity in MPLD estimates. Therefore, Table 3 documents the estimation results of an IV regression that also includes interaction terms with proxies for liquidity-related variables. In particular, deposit growth is interacted with a bank's lagged cash-to-asset ratio, lagged total deposits (log-transformed), the lagged bank-level HHI (as a proxy for deposit market power), and a bank's deposit beta (as a proxy for deposit stickiness).

If liquidity constraints are indeed relevant for banks' MPLD, I expect banks with higher cash-to-asset ratios to have a lower MPLD. Moreover, liquidity constraints also have a liability

[19] It might be tempting to directly compare the IV estimate in column (3) with its OLS counterpart in (1) to infer something about the direction of bias. However, note that the IV estimates—even if both the relevance criterion and the exclusion restriction hold—measure only a *local* average treatment effect (LATE) whereas OLS measures the average treatment effect (ATE). Put differently, the IV estimate measures the MPLD only for the fraction of deposit inflows that was induced by the dividend income instrument. Deposit inflows that would have arrived anyway could, in principle, have a different MPLD altogether.

**Table 3: Heterogeneity in the Marginal Propensity to Lend (MPLD)**

This table contains the results of panel IV regressions at the bank-year level of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks that have a geographical imbalance index (Aguirregabiria *et al.*, 2025) above the median. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD). The interacted variables also enter the regression as standalone regressors, but their estimates are not reported here. For definitions of the lagged interacted variables, see Section 4.

| | Dependent variable: $\Delta Loans$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta Deposits$ × Cash/Assets (lag) | -0.924$^{*}$ | | | | | 0.280 |
| | (0.478) | | | | | (0.655) |
| $\Delta Deposits$ × Log(Deposits) (lag) | | -0.101$^{***}$ | | | | -0.0954$^{***}$ |
| | | (0.0104) | | | | (0.00922) |
| $\Delta Deposits$ × Bank-HHI (lag) | | | -1.366$^{**}$ | | | -0.923$^{**}$ |
| | | | (0.612) | | | (0.433) |
| $\Delta Deposits$ × Deposit $\beta$ | | | | 0.321 | | 0.609$^{**}$ |
| | | | | (0.506) | | (0.259) |
| $\Delta Deposits$ × Leverage (lag) | | | | | 0.00554 | 0.0122 |
| | | | | | (0.0122) | (0.0118) |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bank FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N(Banks) | 2,824 | 2,824 | 2,824 | 2,824 | 2,824 | 2,824 |
| N | 53,492 | 53,492 | 53,492 | 53,492 | 53,492 | 53,492 |

Standard errors (clustered at the bank-level) in parentheses.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

component that depends on the stability of a bank's funding mix.[20] For example, the concentration of deposits in markets where a bank funds itself (measured by the bank's HHI) can serve as a proxy for this funding stability (Li *et al.*, 2023). Depositors in areas with limited bank competition are, everything else equal, more "sticky" than those in areas with high competition (i.e., their $\omega$ is lower). Hence, banks with a higher average HHI should be less liquidity-constrained for a given level of liquid assets, and thus exhibit lower MPLDs. Finally, I expect banks with a larger *stock* of deposits to exhibit lower MPLDs because larger banks mechanically face smaller expected deposit outflows for payment purposes (Parlour *et al.*, 2022), and thus have smaller liquidity needs per deposit.[21]

Table 3 confirms these conjectures, both in columns (1) – (5) and in the "horse race" specification shown in column (6), although the estimated coefficient of the cash-to-asset ratio becomes statistically insignificant in the latter case. The estimate in column (1) implies that a one-standard deviation increase in banks' cash-to-asset ratio is associated with a drop in the MPLD of 0.06. Similarly, a one-standard deviation increase in Bank-HHI implies a decrease in the MPLD of 0.16. Regarding the deposit beta of Drechsler *et al.* (2017, 2021), a one-standard deviation drop (i.e., more sticky deposits) is associated with a decrease in the MPLD of 0.05. Relative to the average MPLD of 0.32, these are economically significant differences, which are further corroborated by the results of a bank-by-bank estimation in Section 6.5 below. Finally, in the kitchen sink specification in column (6), the liability-related variables seem to dominate the cash-to-asset ratio as a determinant of the MPLD.

In contrast, the coefficient of the interaction term with leverage in columns (5) and (6) is statistically indistinguishable from zero. Given that deposit inflows that are settled in cash do not affect banks' risk-weighted assets and thus do not directly relax capital constraints, this finding is not surprising in the context of the model framework introduced in Section 3. Nevertheless, it is noteworthy that leverage does not seem to have a significant effect on the MPLD, even though it is a key variable of interest in the broader empirical banking literature.

[20] The LCR is defined as high-quality liquid assets (HQLA) divided by the projected net cash outflow over 30 days. Note how the cash-to-asset ratio, the bank-HHI, and total deposits can be mapped to $c$, $\omega$, and hence the liquidity constraint in the model in Section 3.

[21] To see this, consider the theoretical limit case where all households hold deposits at one large bank. Any payment from person A to B will create churn among the bank's deposit accounts, but not affect the total stock. With multiple banks, however, smaller banks are faced with a much higher probability that any given $1 of deposits will leave its balance sheet for payments to depositors at other banks. Another proxy for outflow probabilities would be the number of deposit accounts per bank, but unfortunately, the Call Reports only include this variable after 2008.

**Table 4: MPLD for different loan categories**

This table contains the results of panel IV regressions at the bank-year level of the change in different subcategories of bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the the sample includes only banks that have a geographical imbalance index (Aguirregabiria *et al.*, 2025) above the median. *PostQE* is a binary indicator equal to 1 for all years from 2008 onward, and 0 otherwise. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD).

| | (1) $\Delta Loans$ | (2) $\Delta C\&I Loans$ | (3) $\Delta RE Loans$ | (4) $\Delta Consumer Loans$ | (5) $\Delta Other Loans$ |
|---|---|---|---|---|---|
| $\Delta Deposits$ | 1.015*** | 0.0806 | 0.816*** | 0.0743*** | 0.0472 |
| | (0.116) | (0.0650) | (0.0698) | (0.0262) | (0.0387) |
| PostQE=1 $\times$ $\Delta Deposits$ | -0.641*** | 0.0147 | -0.703*** | -0.00349 | 0.0455 |
| | (0.0720) | (0.0651) | (0.0669) | (0.0208) | (0.0330) |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bank FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| N(Banks) | 3,807 | 3,807 | 3,807 | 3,803 | 3,803 |
| N | 66,190 | 66,190 | 66,190 | 66,144 | 66,144 |

Standard errors (clustered at the bank-level) in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## 6.3 Breakdown by loan type

In the Call Reports balance sheet dataset, total loans can be broken down into real estate loans, commercial & industrial loans, consumer loans, and other loans. To better understand the marginal lending behavior of banks, Table 4 breaks down the MPLD analysis by loan category. This is not just a descriptive exercise, but it can help understand which category banks consider as the *marginal* lending opportunity that is just "waiting to be funded". Column (1) repeats the baseline coefficient for total loans from Table 2 for convenience, while columns (2)–(5) show the MPLDs for different loan categories, both before and after the introduction of QE.

The table suggests that in the pre-QE period, when the average bank operated "hand-to-mouth", the MPLDs per category are approximately proportional to the composition of the total bank loan portfolio (see Figure 5). For example, the average MPLD for C&I loans accounts for approximately 9% of the average total MPLD, while C&I loans also represent approximately 10% of the total loan stock for the median bank. In other words, the dividend-induced cash inflow was transformed into different loan categories in proportion to the existing stock of loans. However, in the post-QE period, the large drop in the MPLD is almost exclusively driven by the real estate lending component. In other words, real estate lending has become much less responsive to positive funding shocks at the bank level.

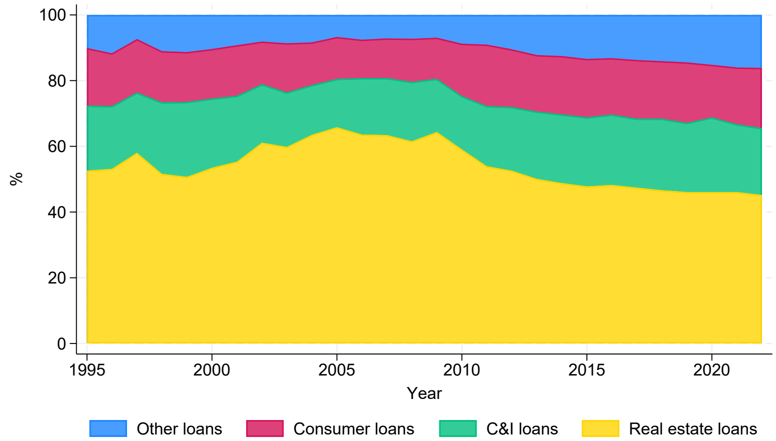



**Figure 5: Composition of U.S. total bank loans over time.** Stacked area chart showing the share of each loan category in total bank loans (in percent) over the period 1994–2021. Categories are real estate loans, commercial & industrial (C&I) loans, consumer loans, and other loans. Data are aggregated across all FDIC-insured institutions. Source: FDIC Call Reports.

One possible explanation for U.S. banks' relatively low post-QE real estate MPLD could be the institutional setup of the U.S. mortgage market. More precisely, the possibility for U.S. banks to securitize and/or sell certain mortgages to government-sponsored entities (GSEs) suggests that banks might treat mortgages akin to standardized commodities rather than a risky asset with diminishing marginal returns. Indeed, Gilje *et al.* (2016) find that banks exposed to deposit inflows related to the U.S. shale oil boom increase mortgage lending, "but only [. . . ] for hard-to-securitize mortgages." I leave a more detailed reconciliation of these findings for future work.

## 6.4 Other balance sheet implications

A natural question to ask in the context of unsolicited deposit inflows is what other balance sheet implications they have beyond the lending response measured by the MPLD. Therefore, I estimate the baseline 2SLS regression again with changes in other broad balance sheet items as the dependent variable. Note that, by construction, (a) the coefficients across all asset categories should sum to the coefficient on total assets in column (1); and (b) the response of bank equity should be the difference between the response of total assets and total liabilities. Hence, this exercise also serves as a consistency check for the baseline MPLD estimates.

The results are depicted in Table 5 and show that every dollar of dividend-induced deposit inflows increase total assets by approx. \$0.94, with \$0.32 going into loans (the MPLD), \$0.24

**Table 5: Response of other balance sheet items**

This table contains the results of panel IV regressions at the bank-year level. Each column uses a different broad balance sheet item as the dependent variable: change in total assets, total loans, cash holdings, securities, other assets, non-deposit liabilities, and equity. In all columns, the change in bank deposits is instrumented by a bank's exposure to county-level dividend income, constructed using pre-period deposit market shares (Bartik-style). Observations are weighted by the inverse of lagged total assets. All specifications include bank and year fixed effects. Standard errors are clustered at the bank level. The sample period is 1995–2021; the sample includes only banks that have a geographical imbalance index (Aguirregabiria *et al.*, 2025) above the median.

| | (1) $\Delta Assets$ | (2) $\Delta Loans$ | (3) $\Delta Cash$ | (4) $\Delta Securities$ | (5) $\Delta Other Assets$ | (6) $\Delta NonDepLiab$ | (7) $\Delta Equity$ |
|---|---|---|---|---|---|---|---|
| $\Delta Deposits$ | 0.942*** | 0.322*** | 0.241*** | 0.357*** | 0.0219 | -0.135*** | 0.0774*** |
| | (0.0404) | (0.0581) | (0.0346) | (0.0511) | (0.0217) | (0.0372) | (0.00714) |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bank FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N(Banks) | 3,807 | 3,807 | 3,807 | 3,807 | 3,807 | 3,807 | 3,807 |
| N | 66,190 | 66,190 | 66,190 | 66,190 | 66,190 | 66,190 | 66,190 |

Standard errors (clustered at the bank-level) in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

into cash, and \$0.36 into securities. Interestingly, on the liability side, deposit inflows appear to crowd out other, non-deposit funding sources, but crowd in equity (potentially due to retained earnings). This finding is important as it further strengthens the interpretation of dividend-induced deposit shocks as *unsolicited*. If banks actively sought funding, e.g., to expand their operations, we would expect deposit inflows to be accompanied by an increase in other liabilities (e.g., wholesale funding) rather than a decrease.

## 6.5 Bank-by-bank estimation

This final part is dedicated to estimating the MPLD separately for each bank, using only within-bank variation over time. Of course, with an annual dataset that spans 27 years, the statistical power of each regression is limited. Moreover, separate time-series regressions prohibit the use of year fixed effects to account for bank-invariant trends. Therefore, the resulting MPLD estimates are likely to be biased and should not be interpreted as precise point estimates.

Despite this limitation, the exercise is useful for two reasons: (a) Bank-by-bank estimates enable policymakers to precisely identify which banks exhibit the highest average MPLD; and (b) interested researchers can use the distribution of estimates as a calibration target for models with heterogeneous banks and deposit withdrawal/inflow shocks as in Bianchi and Bigio (2022).

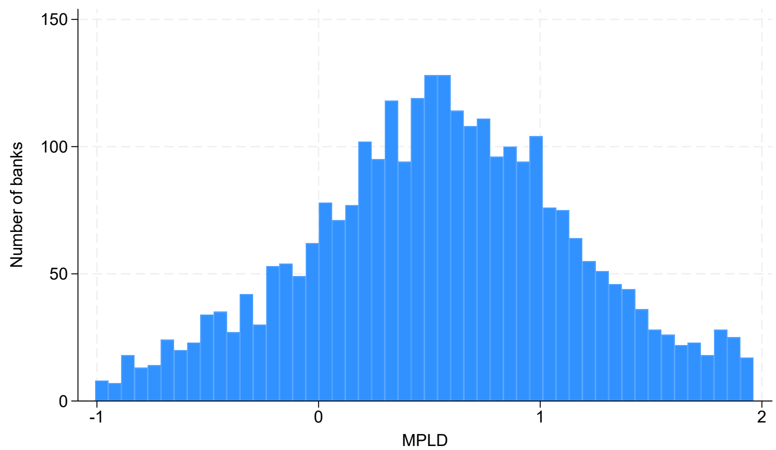



**Figure 6: Distribution of MPLDs.** This table contains the distribution of the marginal propensity to lend out of unsolicited deposit inflows (MPLD), obtained as the regression coefficients of separate bank-by-bank IV regressions of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. The sample period is 1994–2021, and the sample includes only banks that have a geographical imbalance index (Aguirregabiria *et al.*, 2025) above the median and at least 5 annual observations. To remove outliers, the top and bottom 10 percent of the MPLD distribution have been discarded.

To be precise, I estimate the 2SLS regression

$$\Delta Loans_t = \alpha + \beta \, \Delta \widehat{Deposits}_t + \varepsilon_t \tag{10}$$

separately for each bank and collect the corresponding $\hat{\beta}$ estimates. To ensure a minimum number of observations per bank, I drop all banks with fewer than $T_b = 5$ annual observations (which corresponds to the 5$^{\text{th}}$ percentile of the $T_b$ distribution). Moreover, I eliminate the bottom and top 10% of the resulting MPLD estimates to remove outliers. The resulting MPLD distribution is shown in Figure 6.

Three observations stand out: First, the majority of MPLDs lie between zero and one, consistent with the average results in Table 2. Second, a non-negligible amount of banks exhibit MPLDs above one. This suggests that deposit inflows may crowd in other forms of funding or trigger a reallocation of the existing asset portfolio towards loans. Third, there are banks with negative estimated MPLDs, suggesting that deposit inflows may also crowd out loans. Following the logic in Bolton *et al.* (2025), this could be explained by (non-risk weighted) leverage ratio constraints that force banks to deleverage in response to an unsolicited expansion of liabilities.

# 7 Conclusion

This paper contributes to the understanding of banks' marginal propensity to lend out of unsolicited deposit inflows (MPLD) by applying a novel identification strategy based on county-level dividend payouts. The analysis uncovers three main findings. First, the MPLD is on average positive, but time-varying: before the onset of Quantitative Easing (QE), the average U.S. bank operated effectively "hand-to-mouth", with approximately every dollar of exogenous deposit inflows converted into loans—especially to the real estate sector. Since the start of QE, however, the MPLD has declined to approximately 0.37, indicating that liquidity constraints have loosened, though not disappeared. Second, the MPLD strongly varies with liquidity conditions and funding structure: it declines with higher cash-to-asset ratios and deposit market power (as proxied by the deposit Herfindahl index), and increases with deposit beta—a proxy for the "flightiness" of deposit funding. Third, the MPLD displays no significant relationship with leverage, suggesting that what constrains bank lending at the margin is not primarily driven by leverage considerations.

These findings have several policy implications. The presence of "hand-to-mouth" banks implies that even in a system awash with reserves, marginal adjustments in reserve distribution could meaningfully impact credit supply. Conversely, in the context of QT, reserve withdrawals could tighten credit for precisely those banks that are still liquidity-constrained. Moreover, concerns about CBDC-induced deposit flight might be amplified for banks with high MPLDs.

Future research could explore several promising directions. First, it would be valuable to further examine how the MPLD interacts with other forms of constraints, such as risk-based capital requirements, especially during periods of financial stress. Second, it would be beneficial to account for changes in the maturity structure (e.g., savings vs. time deposits) in response to deposit inflows (Supera, 2022). Lastly, integrating the MPLD into macro-financial models with heterogeneous banks could improve our understanding of monetary transmission and help design more targeted policy interventions.

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# Appendix

## A Additional material about bank deposits

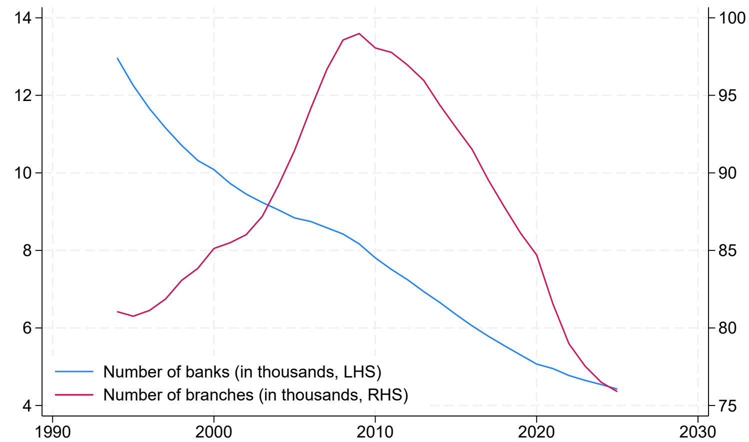



**Figure A1: Number of U.S. banks and branches over time.** Line chart showing the number of unique FDIC-insured commercial banks (left axis, thousands) and the total number of branches (right axis, thousands) in the United States over the period 1994–2022. Source: FDIC Summary of Deposits (SOD).

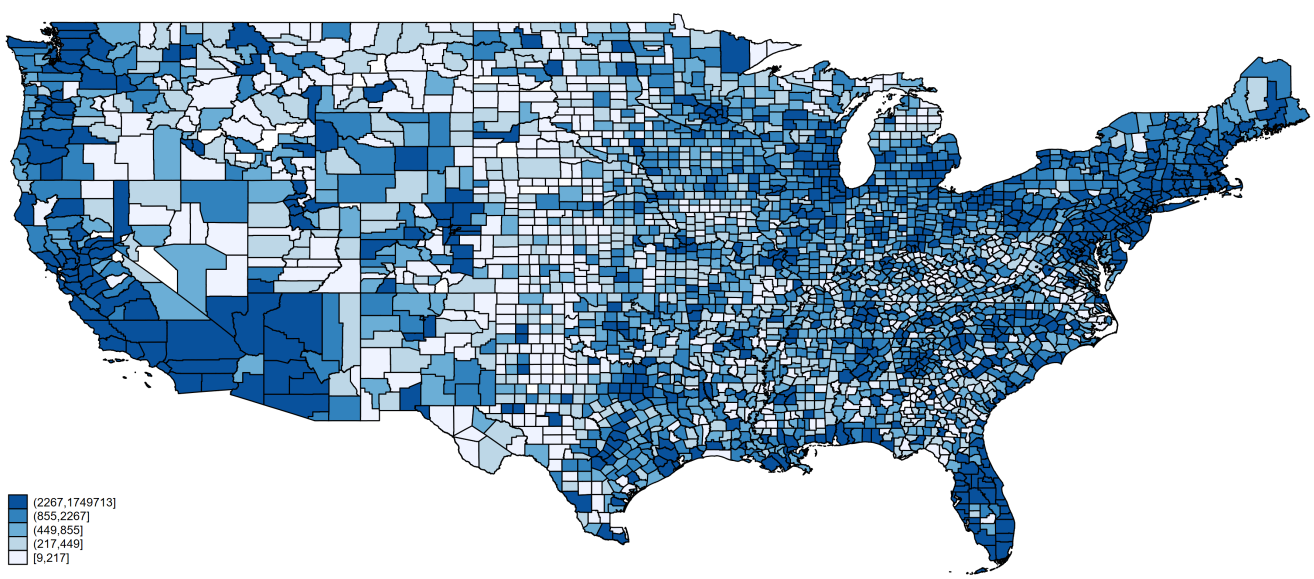



**Figure A2: Bank deposits across U.S. counties.** Map of total bank deposits (millions of USD) across U.S. counties as of June 2022, shaded in five quantile categories (darker = higher deposits). The map covers the contiguous 48 states; Alaska, Hawaii, and U.S. territories are excluded. Source: FDIC Summary of Deposits (SOD).

# B Imbalance Index: Construction and Coverage

## Formal definition

Following Aguirregabiria *et al.* (2025), the imbalance index (II) for bank $j$ in year $t$ is defined as

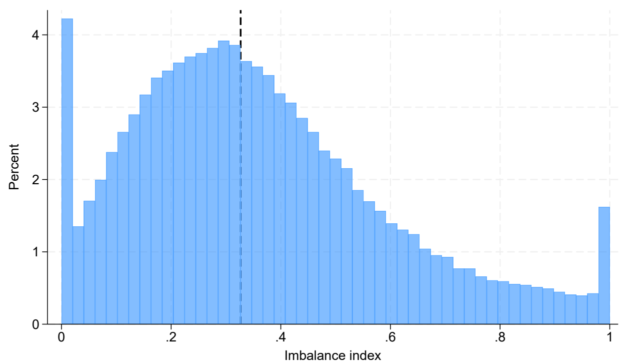
$$\mathrm{II}_{jt} = \frac{1}{2}\sum_{m}\left|\frac{q^{l}_{jmt}}{Q^{l}_{jt}} - \frac{q^{d}_{jmt}}{Q^{d}_{jt}}\right|, \tag{11}$$

where $q^{l}_{jmt}$ and $q^{d}_{jmt}$ denote mortgage origination volume and deposit volume of bank $j$ in county $m$ at time $t$, and $Q^{l}_{jt} = \sum_m q^{l}_{jmt}$, $Q^{d}_{jt} = \sum_m q^{d}_{jmt}$ are the bank-year totals. The II equals zero when the geographic lending and deposit distributions are identical and approaches one when they are fully segregated.

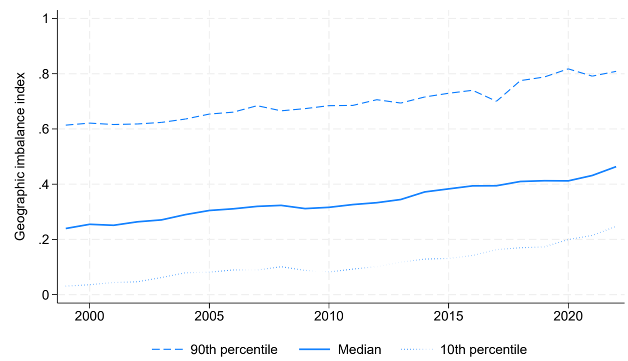
## Construction

Deposit volumes by county are taken from the FDIC SOD, aggregated to the bank-county-year level as described in Section 4. Mortgage origination volumes come from HMDA loan-level records covering 1999–2021. I retain only originated loans (action taken = 1) by depository institutions supervised by the OCC, Federal Reserve, FDIC, or OTS (agency codes 1–4).

HMDA filers are identified by a respondent ID and agency code before 2018, and by a Legal Entity Identifier (LEI) from 2018 onward. I construct a crosswalk to FDIC Certificate Numbers (CERTs) using the FDIC BankFind Suite: for pre-2018 data, respondent IDs are matched by OCC charter number (agency 1), Federal Reserve RSSD ID (agencies 2 and 9), FDIC CERT directly (agency 3), and OTS docket number (agency 4); for 2018 onward, LEIs are matched via the FDIC BankFind institution database. Many pre-2018 HMDA filers are non-depository institutions (e.g., independent mortgage companies) without an FDIC CERT; after excluding unmatched filers, the matched share of origination volume is approximately 30–40% for pre-2018 years and above 90% for 2018 onward. Only loans matched to a CERT also appearing in the SOD are retained.




**(a)** Distribution of II across bank-year observations




**(b)** Evolution of II percentiles over time

**Figure A3: Distribution of the imbalance index.** Panel (a) shows the distribution of the self-computed imbalance index (II) across all bank-year observations in the sample. The vertical dashed line marks the median imbalance index. Panel (b) shows the 10th, 50th, and 90th percentiles of the II distribution for each sample year. Source: author's calculations based on HMDA and FDIC SOD data.

# C Robustness Checks

## C.1 Sensitivity of OLS vs. IV estimates to bank sample selection

### Table A1: OLS vs. IV estimates for different imbalance index thresholds

This table contains the results of panel OLS and IV regressions at the bank-year level of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks with an "imbalance index" (Aguirregabiria *et al.*, 2025) above a certain percentile, where this cutoff is gradually increased from column to column. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD).

| | II $\geq$ p25 | | II $\geq$ p50 | | II $\geq$ p75 | | II $\geq$ p90 | |
|---|---|---|---|---|---|---|---|---|
| | (1) OLS | (2) IV | (3) OLS | (4) IV | (5) OLS | (6) IV | (7) OLS | (8) IV |
| $\Delta Deposits$ | 0.417*** | 0.343*** | 0.408*** | 0.322*** | 0.415*** | 0.418*** | 0.413*** | 0.654*** |
| | (0.0456) | (0.0559) | (0.0504) | (0.0581) | (0.0531) | (0.0830) | (0.0998) | (0.0943) |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bank FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| F | 84 | 38 | 66 | 31 | 61 | 25 | 17 | 48 |
| N(Banks) | 5,690 | 5,690 | 3,807 | 3,807 | 1,989 | 1,989 | 843 | 843 |
| N | 99,287 | 99,287 | 66,190 | 66,190 | 33,090 | 33,090 | 13,245 | 13,245 |

Standard errors (clustered at the bank-level) in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$